

Weed management decision models: pitfalls, perceptions, and possibilities of the economic threshold approach

Gail G. Wilkerson

Corresponding author. Crop Science Department,
Box 7620, North Carolina State University, Raleigh,
NC 27695-7620; gail.wilkerson@ncsu.edu

Lori J. Wiles

USDA-ARS-WMU, AERC—Colorado State
University, Fort Collins, CO 80523

Andrew C. Bennett

Everglades Research and Education Center, 3200
East Palm Beach Road, Belle Glade, FL 33430-4702

The use of scouting and economic thresholds has not been accepted as readily for managing weeds as it has been for insects, but the economic threshold concept is the basis of most weed management decision models available to growers. A World Wide Web survey was conducted to investigate perceptions of weed science professionals regarding the value of these models. Over half of the 56 respondents were involved in model development or support, and 82% thought that decision models could be beneficial for managing weeds, although more as educational rather than as decision-making tools. Some respondents indicated that models are too simple because they do not include all factors that influence weed competition or all issues a grower considers when deciding how to manage weeds. Others stated that models are too complex because many users do not have time to obtain and enter the required information or are not necessary because growers use a zero threshold or because skilled decision makers can make better and quicker recommendations. Our view is that economic threshold-based models are, and will continue to be, valuable as a means of providing growers with the knowledge and experience of many experts for field-specific decisions. Weed management decision models must be evaluated from three perspectives: biological accuracy, quality of recommendations, and ease of use. Scientists developing and supporting decision models may have hindered wide-scale acceptance by overemphasizing the capacity to determine economic thresholds, and they need to explain more clearly to potential users the tasks for which models are and are not suitable. Future use depends on finding cost-effective methods to assess weed populations, demonstrating that models use results in better decision making, and finding stable, long-term funding for maintenance and support. New technologies, including herbicide-resistant crops, will likely increase rather than decrease the need for decision support.

Key words: Bioeconomic models, decision support systems, computer decision aids.

With the release of 2,4-D in 1944, the modern era of weed control began. Public spending on weed-related research climbed from \$0.8 million in 1950 to \$2.3 million in 1957 (Ennis 1958), and herbicide use climbed from 23 million acres of field crops in 1949 to 48 million acres in 1959 (Ennis 1960) and over 185 million acres in 2000 (National Agricultural Statistics Service 2001). By the late 1950s, many herbicide choices were available to growers, and weed scientists were conducting and publishing numerous studies exploring the efficacies of new herbicides and the effects of weather, soil moisture, soil type, weed species, weed height, planting date, herbicide formulation and carrier, application rate, and other factors on efficacy (e.g., Blouch and Fults 1953; Foy 1954; Freed 1951; Indyk 1957; Scott et al. 1954; Slife 1956). Losses caused by weed competition also were being assessed (e.g., Shadbolt and Holm 1956), as well as the economic returns from alternative management strategies (e.g., Holstun et al. 1960; Nyland et al. 1958). The development of weed management decision models, however, began only after the economic threshold was introduced as a concept of pest management and computers became a tool for farm management.

The economic threshold concept was introduced by Stern et al. (1959) and was beginning to be accepted by entomologists by the early 1970s (Stern 1973). Because crops are frequently attacked by only one insect species at a time,

the development and implementation of economic thresholds for insect management is, in some ways, a straightforward process. However, Stern (1973) noted that complicating factors, such as rapid resurgence of the pest species or an outbreak of a secondary pest species after treatment because of the elimination of natural enemies of the secondary species, can make determining an economic threshold difficult. Entomologists have accepted scouting and the use of economic thresholds as an important component of insect pest management, despite the difficulties involved (Metcalf 1980). A survey sent in 1988 to members of the Entomological Society of America who held extension appointments in the United States during 1972 and 1988 (162 on the 1972 list and 295 on the 1988 list) found that 20% of respondents on the 1972 list and 68% of respondents on the 1988 list thought that scouting and thresholds had been a very important influence on their activities, and 71% of all respondents thought that these would be very important in the future (Allen and Rajotte 1990).

Adoption of an economic threshold approach to weed management has been much slower. The multispecies nature of the weed population in most fields has complicated the application of this concept because both crop yield loss and herbicide efficacy are species dependent and weeds interfere with each other as well as with the crop. Although economic thresholds were determined for some individual species in

TABLE 1. Questions and responses to the Web survey of members of selected U.S. professional weed science societies conducted during May and June 2001.

Question	Response	Count	Percent
1. Are you aware of any computer software or models that are being used to aid in making weed management decisions (outside of research)?	Yes	28	50
	No	28	50
2. Are you aware of any computer software or models that are being developed to aid in weed management decision making?	Yes	23	41
	No	33	59
3. Do you think computer software and models can be beneficial in making weed management decisions?	Yes	48	82
	No	8	14
	No opinion	2	4
4. Are you involved in any area related to weed management decision software or models?	Yes	30	54
	No	26	46
5. If the answer to Question 4 is yes, please indicate the area of involvement	Data	24	80
	Research testing	17	60
	Development	13	43
	On-farm testing	11	40
	Support	7	23
	University research	18	32
6. Please indicate your primary occupation	Extension	14	25
	Government research	7	12
	Industry research	4	7
	Agricultural consultant	3	5
	Industry sales	3	5
	Student	3	5
	Local government weed and pest control	1	2
	Regulatory	1	2
	Teaching and administration	1	2
	University extension and research	1	2
7. Please indicate your areas of involvement or specialization	Field crops	45	80
	Herbicides	38	68
	Horticultural crops	18	32
	Forage crops	12	21
	Invasive weeds	8	14
	Application technology	6	11
	Biological control	6	11
	Range management	6	11
	Turf	6	11
	Aquatic weeds	4	7
	Other	11	20

the 1970s (e.g., Anderson and McWhorter 1976; Barrentine 1974; Coble and Ritter 1978), practical implementation of economic thresholds in weed management rested upon maturation and increasing availability of computer technology in the 1980s. Since Marra and Carlson (1983) published an economic threshold model for weeds in soybean [*Glycine max* (L.) Merr.], numerous decision models have been developed and many have been made available to extension personnel, growers, and other decision makers.

The objectives of this article are to review the development and use of computer models for weed management decision making with primary emphasis on those that incorporate economic thresholds, to consider the constraints and challenges that have hindered wide-scale use of these models, and to speculate about the future of weed management decision models.

Materials and Methods

In May 2001 a survey about weed management decision models was constructed and made available to the weed science community over the World Wide Web for a period of 6 wk. Members of the Weed Science Society of America, the Southern Weed Science Society, and the Western Weed Science Society were notified by e-mail of this survey and given an opportunity to state their views on the usefulness of bioeconomic models for decision making. Questions included in the survey are presented in Table 1. If respondents answered affirmatively to Questions 1 or 2 (i.e., they knew of weed management decision models being used or developed), they were asked to provide contact information for model developers. Respondents were also given the opportunity to enter comments under Question 3. This survey

was not intended to yield a scientific sampling of members' opinions or to gauge the perceptions of potential model users because we surveyed only members of professional weed science societies. Rather, it was designed to help identify development efforts that might not yet have been published and to give weed scientists with strong opinions (pro or con) about the usefulness of these models an opportunity to contribute their thoughts about the potential benefits and pitfalls. We devote a large portion of this article to the comments provided by survey respondents because we think that they reflect the major currents of thought that we have encountered during our years of working with these models. In this article, we first review the modeling literature, then summarize the perceptions of other weed scientists, as reflected in survey responses, and then present our own perspectives on the issues raised and future possibilities.

Review of Models

Several review articles dealing with the use of models in weed management have been published. Cousens et al. (1987b) classified models developed to predict changes in weed populations as long term (greater than a year) or short term (dealing with particular phases of the weed life cycle of less than a year) and reviewed functional forms that had been used in simulating weed population dynamics in cereal crops. Doyle (1991) reviewed mathematical models and discussed them in terms of success in addressing five key issues: likelihood of invasion, rate of spread, crop competition, effectiveness of control, and cost of control. Doyle (1997) discussed the role of mathematical modeling in developing integrated strategies, involving reduced dependence on chemicals, for controlling weeds and other pests. Lundkvist (1997) noted that models have been categorized in a number of ways, and grouped them into those that have followed primarily a research approach and those that have followed a more practical approach. Mortensen and Coble (1991) categorized decision aid software based on herbicide efficacy or seed bank and seedling population estimates. In this current review we focus on models that have been designed primarily for use by decision makers, in particular those models that consider not only the efficacy of control measures but also biological and economic factors. We refer readers to the previously cited review articles for more information on models not included in this article.

Although there is considerable diversity in the models that have been developed to date, those that take economics as well as biological factors into account share certain key components: (1) they require information from the user regarding the nature of the weed populations present in the field; (2) on the basis of user input, they calculate expected crop yield loss caused by weed interference both before and after weed control measures have been implemented; and (3) they estimate potential economic returns for each available control measure using information about the costs and efficacies of these measures, the expected weed-free yield, and the crop's market value.

Quantifying Weed Populations

By far, the most common approach to quantifying field weed populations for use in decision models has been to use weed density per unit ground area or per length of row

(Aarts and de Visser 1985; Auld and Tisdell 1987; Berti and Zanin 1994, 1997; Black and Dyson 1993; Cousens et al. 1987a; Gerowitt and Heitefuss 1990; Keisling et al. 1984; King et al. 1986; Krishnan et al. 2001b; Kwon et al. 1995, 1998; Lybecker et al. 1991a; Marra and Carlson 1983; Martin et al. 2001; Mortensen et al. 1993; O'Donovan et al. 1999; Pannell 1990; Pannell et al. 2000; Schribbs et al. 1990; Stigliana and Resina 1993; Streibig 1989; Sturgill et al. 2001b; Swinton and King 1994; Wiles et al. 1996; Wilkerson et al. 1991). In most cases, average weed densities of individual species serve as model input for a field, although users are advised to generate separate recommendations if the weed population is very different in some areas of the field (Sturgill et al. 2001b). Several models have incorporated soil seed bank information, particularly when the model addressed the application of preplant-incorporated or preemergence herbicides (King et al. 1986; Lybecker et al. 1991a; Schribbs et al. 1990; Swinton and King 1994; Wiles et al. 1996). To simplify user input, some developers have grouped weed species into broad categories of broadleaved or grass (King et al. 1986; Lybecker et al. 1991a) or have used these broad categories for most species but have separated a few troublesome species for special consideration (Aarts and de Visser 1985). Another method for simplifying model input requirements has been to ask for density information in ranges (e.g., low, medium, high) (Mortensen et al. 1999; Wilkerson et al. 1999).

In a few cases, measures other than density have been used to quantify weed populations. Gerowitt and Heitefuss (1990) used percent ground cover to assess broadleaf weeds. Kropff and Spitters (1991) and Lotz et al. (1996) used relative leaf area (leaf area index of a weed species as a fraction of the total leaf area of all species) in equations to predict yield loss.

Estimating Yield Loss

From the beginning of weed management decision model development efforts, investigators have been aware that the relationship between weed density and yield loss is nonlinear and that weeds interfere with each other as well as with the crop. Marra and Carlson (1983) fit linear, quadratic, and log-log equations to data from weed interference studies and found that for all species evaluated a nonlinear relationship was highly significant. Keisling et al. (1984) fit a cubic response surface that predicted yield loss as a function of weed density, duration of interference, and competitive ability of the different species. A few models have used a logistic equation to describe yield loss as a function of weed density (King et al. 1986; Kwon et al. 1995; Lybecker et al. 1991a). O'Donovan et al. (1999) incorporated crop density, as well as weed density, into a nonlinear regression equation to estimate crop yield loss. Cousens (1985) compared 18 different functional forms for describing crop yield loss as a function of weed density. He determined that of the two-parameter models, a rectangular hyperbola fit the data best and concluded that a two-parameter model was generally sufficient. Since that time, many model developers have used the rectangular hyperbola or a form of the hyperbola modified to incorporate the effect of the time interval between crop and weed emergence (Cousens et al. 1987a) to predict yield loss. Swinton and Lyford (1996) examined the conditions necessary to determine if a four-parameter sigmoidal crop

yield loss equation could provide a better fit to field data than does the two-parameter hyperbolic equation and concluded that a much larger data set would be required to fit the sigmoidal function than is normally available from agronomic experiments.

Various methods have been used to account for multispecies weed interference. Keisling et al. (1984) calculated yield loss by subtracting the percent loss from the most competitive weed and then repeated this procedure for each remaining weed species. Coble (1986) defined a crop- and weed-specific competitive index (CI) that ranked degree of competitiveness on a scale from 0 to 10. Yield loss from a multispecies weed population was computed by multiplying weed density by CI for each species, summing across species to calculate a total competitive load (TCL), then using TCL to estimate percent yield loss. This approach has been used in HERB[™] (Coble and Mortensen 1992; Wilkerson et al. 1991), NebHERB (Mortensen et al. 1993), GWM (Wiles et al. 1996), HADSS[™] (Sturgill et al. 2001b), and WeedSOFT[™] (Krishnan et al. 2001b; Mortensen et al. 1999). Black and Dyson (1993) represented the relative competitive abilities of annual weeds on a scale from zero to one and calculated weed units in a manner similar to that used to calculate TCL. In an approach that is functionally equivalent to computing TCL, Berti and Zanin (1997) converted the density of each weed species into a "density equivalent," defined as the density of a reference species that would cause the same yield loss as caused by the observed weed at its density. Aarts and de Visser (1985) assigned Standard Weed Units to various weed species by dividing 500 by the maximum number of plants per square meter that could be tolerated. They then summed Standard Weed Units across species and determined whether control measures were justified, based on whether the sum was above the total tolerable Standard Weed Units. Swinton and King (1994) used a multivariate formulation of the hyperbolic yield equation to account for multispecies competition, and Swinton et al. (1994) used data from 13 Minnesota and Wisconsin data sets to estimate model parameters for several weed species. They found that the coefficient estimates were stable over years but not locations.

Economic Considerations

Once yield losses with and without weed control have been estimated, the return (R) for a specific treatment j is frequently determined by a formula such as the following:

$$R_j = [P \times (L_0 - L_j)] - (C_j + A_j) \quad [1]$$

where P is expected crop-selling price, L_0 is expected yield loss if no weed control is used, L_j is expected yield loss after treatment j is applied, C_j is cost of treatment j , and A_j is the cost of applying treatment j (Wilkerson et al. 1991). This method for calculating economic return does not take into account any effects on future crops, such as additions to the seed bank from weeds not controlled by treatment j that may raise control costs in future years. Several models have incorporated effects of treatments across years (King et al. 1986; Pannell et al. 2000; Schribbs et al. 1990; Swinton and King 1994) by considering seed bank dynamics. Aarts and de Visser (1985) lowered the treatment threshold for certain weed species if they were known to be difficult to control in the following crop.

Integrating—Organizing—Presenting Information

A primary aim of decision model developers has clearly been to organize and present relevant biological and economic information that facilitates field-specific decision making. Although many models have been presented as economic threshold models, in reality most do more than just determining whether or not the weed population in a given field is above an economic treatment threshold. Most programs include information on many different control measures, and although they may rank treatments according to expected net returns, they provide information on alternatives to the top treatment and may allow the user to sort by expected crop yield after treatment (Martin et al. 2001), treatment cost (Bennett et al. 2000; Sturgill et al. 2001b), or efficacy against the total weed complex or a particular weed species (Bennett et al. 2000; Sturgill et al. 2001b). Because herbicides are by far the most prevalent means of weed control for field crops in the United States, decision models have focused on herbicides. However, some models also consider mechanical or cultural control methods where appropriate (Berti and Zanin 1997; Martin et al. 2001; Pannell et al. 2000; Stigliana and Resina 1993; Swinton and King 1994; Wiles et al. 1996). A number of decision models provide information about potential environmental effects and risks for alternative treatments: GESTINF (Berti and Zanin 1997), WeedSOFT[™] (Krishnan et al. 2001b; Martin et al. 2001), and WeedMAK (J. D. Green et al., personal communication). In some cases, rates for soil-applied herbicides are calculated on the basis of soil type and organic matter (Lybecker et al. 1993). Information about rotational restrictions, potential crop injury, and label restrictions may be presented to the user, or treatments may be eliminated from evaluations on the basis of these restrictions (Lybecker et al. 1993; Sturgill et al. 2001b; Wiles et al. 1996). Some models include information and pictures to help users identify weed seedlings (Martin et al. 2001; Rydahl 1999).

Survey Results

Fifty-six people responded to the Web survey (Table 1). Over 50% of the respondents were involved in model development, data collection, or validation efforts. Eighty-two percent thought that computer models and software could be beneficial in weed management decision making. Of the models that were identified, WeedSOFT[™] (Krishnan et al. 2001b; Mortensen et al. 1999) was mentioned by 12 respondents, HERB[™] or HADSS[™] (Sturgill et al. 2001a, 2001b; Wilkerson et al. 1991) by 10, WeedMAK (J. D. Green, personal communication) and AgroManager (Denise Maurice, personal communication; a threshold model developed by O'Donovan et al. 1999) by 2, and all others by 1. Many respondents, even those that answered Question 3 in the affirmative, had reservations about decision models or the use of the models. These comments are summarized in the subsequent sections.

Perceptions: Value and Expected Value

Models Have Educational Value

Respondents to our survey in general seemed to be much more comfortable with the use of models as educational

tools than as real-time decision aids. Survey respondents suggested that models can be used to teach the principles of weed management, economic thresholds, weed competitiveness and the effect of weeds on crop production, herbicide efficacy, and the lessening effects and increasing threshold for later-emerging weeds. Use of models can heighten understanding of weed biology and ecology. Models can be especially valuable for younger or inexperienced growers and agents, by helping them to understand the complexities in selecting a weed management program. Running “what if” scenarios can be useful even for experienced decision makers, by helping them to address unfamiliar weed problems and to evaluate the relationship of new treatments to those with which they are already familiar.

Models as Decision-Making Tools

Several survey respondents noted that using models can improve weed control by predicting yield loss, determining if a herbicide treatment is economically justified in the current year, comparing herbicide programs, and selecting the type and rate of herbicide to use in a given situation or on a specific soil type. Respondents also noted that using a decision aid can reduce the application of unnecessary herbicides, lessen the potential for detrimental environmental effects, reduce the occurrence of carry-over damage to the next crop, improve herbicide rotation, and minimize crop injury. One individual noted that a particular model had been tremendously successful by allowing growers to decide when and what to spray and had reduced calls to extension personnel. Another noted that the use of decision-making software could improve the image of the pesticide applicator–producer in the eyes of the public and regulatory agencies.

Harsh et al. (1989) noted that a model (1) is often useful to keep all the facts necessary for decision making in proper relationship to each other; (2) is valuable because it can be used to perform “what if” analyses when there is uncertainty about factors influencing the decision; and (3) ideally, can capture and convey a large quantity of expert knowledge that is carefully focused on the problems confronting decision makers. All these points were mentioned by survey respondents. They noted that there is much to remember when making a weed control decision and that a model can help with getting to the right choices without unexpected consequences and without mistakes caused by oversight. Models can integrate information from various sources, perform rapid calculations, help with forecasting what may happen in particular weed management situations, help in understanding complex interactions, help with controlling unusual weeds and using new or less well-known treatments, and show the potential benefit of “inexpensive” vs. “expensive” treatments.

Keisling et al. (1984) suggested that models could help in weed management planning, and they indicated that their model could be used to identify fields with the most damaging weed populations that needed to be treated first because crop yield loss increases, the longer weeds are left in the field and the higher the weed density. Survey respondents also mentioned the potential usefulness of models in planning, both for evaluating weed management systems and for anticipating spray scheduling.

Several survey respondents mentioned the value of models

in implementation of precision agriculture (site-specific weed management). They pointed to the importance of models in evaluating the effects of weed spatial distribution across a field, in identifying the best treatment and rate for each section of the field, and in avoiding unnecessary herbicide applications in certain portions of the field.

Perceptions: Problems and Pitfalls

Current Decision Models Are Too Simple

From a biological standpoint, the two primary concerns of some survey respondents are that decision models generally ignore the patchy, nonuniform, spatial distribution of many weed populations, and they do not incorporate the effect of weed escapes on the weed seed bank or problems in future crops when calculating an economic treatment threshold and evaluating treatments.

Models, by definition, are simplifications of real systems and, as such, will not include all the factors that influence weed–crop interactions. Some survey respondents indicated that currently available models are too simple because they do not consider the effects of cultural practices (e.g., crop variety, row spacing) on weed competitiveness when making recommendations and do not incorporate alternatives to herbicides or adjust herbicide efficacy values in response to all the factors that are known to affect efficacy. However, one survey respondent took issue with the inclusion of cultivation in one model, stating that cultivation often came up as the cheapest option but that the model neglected the hidden costs of possible soil moisture loss and erosion after cultivation. Another individual noted that local differences in crop varieties, yield potential, and other factors would cause any system with universal application to be very complex.

Survey respondents also thought that the models are too simple because they do not or cannot include all the factors that growers consider when reaching a decision. They noted that grower decisions include too many judgment factors and life situation variables for the models to be useful; growers are more interested in simplicity (e.g., using the same treatment on multiple fields) and effectiveness of the weed management program than in potential economic returns, and chemical manufacturers’ or distributors’ marketing programs that bundle seed and application together with discounted herbicides make it difficult to assign prices to herbicides for use in decision models.

Models Require Too Much Information and Are Not Accurate

Just as many survey respondents thought that current models are too simple, others thought that the models are too complex and require too much information from the user. In particular, respondents indicated that collecting scouting data and entering all the information required by the models to obtain a recommendation require more time than most decision makers are willing or able to commit. The accuracy of scouting data was also a matter of concern because (1) recommendations from a decision aid are no better than the quality of the scouting and other input information provided by the user, and (2) it may cost more to do a thorough and accurate job of scouting than just to

spray. Several survey respondents expressed the opinion that the models themselves are currently too inaccurate to be of value in real-time decision making because insufficient data have been used in model development for them to accurately predict competitive effects and yield losses in most situations. One person questioned the validity of economic thresholds, stating that the statistics are seldom good enough to prove beyond a doubt that a threshold is above zero.

Models Are Not Necessary

Three reasons were mentioned by survey respondents for believing that models are not necessary: (1) farmers use a zero threshold, so there is no need for an economic threshold model; (2) the availability of glyphosate-resistant crops has eliminated the need for models in these crops; and (3) an expert can make better and quicker recommendations without the tedious collection and entry of a large amount of data into a computer. One survey respondent noted that weed control decisions are almost always for a broad spectrum; species, weed pressure, and threshold are irrelevant because all fields are always sprayed.

Models Are Difficult to Sustain

Survey respondents noted that it can take a very long time to develop a model, and the expense to improve and maintain a model does not compare favorably with the sales potential. One person was aware of two instances in which good computer decision aids did not succeed over the long term. Another individual suggested that models would be adopted only if they were developed by industry and proven to increase profits and reduce costs and litigation.

Our Perspective

Models are and will continue to be valuable decision tools. Weed scientists have long recognized the complexity of making weed management decisions and have used a number of methods for assisting growers and other decision makers with this task, including training sessions for agricultural extension agents and consultants, grower meetings, on-farm trials, field days, and publication of extension bulletins and agricultural chemical manuals. In recent years information increasingly has been made available over the Internet. It has not been the intent of computer model developers to supplant these methods for assisting in complex decisions but rather to supplement them. Most model developers are careful to remind users that the model is a decision aid and not a decision maker (e.g., Krishnan et al. 2001b; Mortensen et al. 1999; Stigliana and Resina 1993; Sturgill et al. 2001b; Wilkerson et al. 1991).

As model developers, we are well aware that growers consider many things when making these complex decisions and that our models cannot incorporate every factor, nor should they. What we hope to accomplish by making models available to decision makers is to provide appropriate, situation-specific information that we and many weed scientists consider to be essential to rational decision making. Although a grower may choose a weed management program based on simplicity or effectiveness, a decision model may help the grower determine the price paid for simplicity and

whether the program is really more effective than alternatives that cost less.

Experts can indeed evaluate the weed problem in a field and make quick and effective recommendations. Model developers have attempted to capture and quantify as much of this expertise as possible: to involve knowledgeable research and extension weed scientists, as well as extension agents and consultants, in development, validation, and evaluation of the models (e.g., Bennett et al. 2000; Krishnan et al. 2001a; Stigliana and Resina 1993). One of the greatest values of computerized decision aids may lie in the ability to capture this knowledge and bring some part of the expertise from many individuals to bear on field-specific questions. In an ideal world, every decision maker would have ready access to a high level of expertise in making these complex decisions. In reality, with reductions in extension service personnel in many states in recent years and with the assignment of new responsibilities to the agents that remain, access to unbiased, field-specific expertise is increasingly available only to those who can afford to pay for it, and only true for high-value crops.

Complexity and Accuracy of Decision Models

Decision model developers have long struggled with the issue of how much biological, ecological, and economic complexity is to be included. This is why decision models differ in how recommendations are generated and what information is displayed to the user. We believe that most model developers would agree that the models could be improved by including additional practices and factors in the decision-making process, but these enhancements are hindered by a lack of data. We are also very aware of the trade-offs involved in making models more complex. As a model becomes more complicated, user input requirements will likely increase, user-friendliness may decline, more information will have to be displayed to help users understand the differences between treatments, validation will be more difficult, and more information will be required from weed science experts each time model databases are updated.

Although weed scientists with whom we have worked appear fairly comfortable with ranking weed species in terms of competitive ability and providing efficacy values for alternative herbicide treatments under varying conditions, they are rightly hesitant to add model components outside the bounds of their own experience, or in cases where they feel too little research has been done, or when results have been too variable, or are too subject to weather conditions or other environmental factors. For example, several weed scientists we consulted were reluctant to provide estimates of the effectiveness of nonherbicidal means of control. Although several models have included mechanical or cultural control methods (Berti and Zanin 1997; Martin et al. 2001; Pannell et al. 2000; Stigliana and Resina 1993; Swinton and King 1994; Wiles et al. 1996), including these is difficult because of a lack of data and variability in results from year to year and location to location because of climatic and environmental factors.

Given the disadvantages and difficulties of making weed management models more complex, the guide for adding complexity must be whether the quality of decision making will be improved. A weed management option is typically optimal for a range of weed populations and other condi-

tions. Even when weed ecology and control may be predicted more accurately by adding complexity to a model, the quality of the recommendations may not be improved. Inaccuracies may not be as damaging for decision making as perceived.

Spatial Distribution

Most decision models do not consider weed spatial distribution when making whole-field recommendations (as opposed to site-specific recommendations). In many cases the assumption of uniform weed spatial distribution may not adversely affect the quality of the whole-field recommendations that are made by the models. In a study using the decision model HERB[™] and scouting data from 14 North Carolina soybean fields, Wiles et al. (1992b) found that the cost of assuming a regular weed distribution was generally low. Although assuming a regular weed distribution resulted in an overestimation of yield loss without control (in some cases a very large overestimation), the optimal treatment was still selected. Recently, analysis of scouting data from over 50 peanut (*Arachis hypogaea* L.) fields in North Carolina yielded similar results (D. Jordan et al., personal communication) to those of Wiles et al. (1992b). In general, for a herbicide treatment to be recommended by an economic decision model, the treatment must not only be cheaper than those with similar efficacy, it must be very effective against the most competitive weeds present in the field. Therefore, after treatment, expected weed populations are very low, weeds are less likely to interfere with each other, and assuming a uniform weed spatial distribution is a reasonable simplification.

Weed Seed Bank Dynamics

The concern about weed seed bank buildup from weed escapes and its effect on the determination of an economic threshold has been addressed by a number of studies through modeling and simulation experiments. Norris (1999) reviews these studies and states that the economic optimum threshold (one that optimizes returns over multiple years) is lower than the economic threshold. He recommends a no-seed threshold, i.e., no weeds are allowed to survive to produce seed. Decision model developers have dealt with this issue in at least three different ways: (1) they have included weed seed bank dynamics in the model (Pannell et al. 2000; Swinton and King 1994); (2) they have raised the CIs for certain weed species in order to incorporate concerns about seed production into the economic threshold (an approach used in both HERB[™] and HADSS[™]); or (3) they have provided a way for users to sort treatments by efficacy or yield after treatment (Bennett et al. 2000; Martin et al. 2001; Sturgill et al. 2001b) so that users can select the most effective treatment, regardless of cost. Incorporating seed bank dynamics into a decision model requires extensive information that is not available for most weed-crop combinations. It also requires assumptions about future environmental effects on seed survival and germination. Information about future crop rotation, tillage, and other management practices that influence weed population dynamics is also necessary.

Scouting Data

Collection of scouting data is indeed a major constraint to acceptance of decision models. The cost, accuracy, and time requirements of counting weeds are concerns, especially if many fields must be assessed quickly. Berti and Zanin (1997) recommend identifying species and determining weed densities in 25- by 30-cm areas at 20 to 30 locations per field for GESTINF. Sturgill et al. (2001b) recommend identifying and counting weeds in 9.3-m² areas in 10 to 12 locations per field for HADSS[™]. Mortensen et al. (1999) recommend assessing weed populations in 5 to 10 locations in 9.3-m² areas, but they also give users of WeedSOFT[™] the option of entering density estimates by categories (very low, low, moderate, etc.) and they state that density assessment is hotly debated.

Several studies have examined ways to simplify this process and to balance the value of information collected vs. the cost of collecting it. King et al. (1998) provided an excellent example of how the value of information can be assessed and reviewed studies that have been done. Gold et al. (1996) found that binomial sampling may be a viable alternative to full-count random sampling. Krueger et al. (2000) performed an economic analysis of binomial sampling for weed scouting and determined that for small fields (10 ha or less) it may yield decisions that are equal to those determined through full-count sampling with less investment of time. Recent studies in North Carolina (D. Jordan et al., personal communication) indicate that sampling in as few as three locations per field may be acceptable for many peanut fields, but the challenge remains of determining how to distinguish these fields from those that require more intensive scouting. Identifying an appropriate scouting plan for use with a decision model may be further complicated by variation in the spatial distribution of weeds between fields. The accuracy of a recommended scouting plan will vary with the spatial distribution of the observed population (Ambrosia et al. 1997; Gotway et al. 1996) or, conversely, the best way to scout will depend on the spatial distribution of the weed population (Burrough 1991).

There will always be some cost associated with assessing weed populations. How users will collect information about weed populations must be considered by model developers. It is important to note that collection of much of the data required for decision models is already necessary if the decision maker is practicing good weed management. However, some of the components such as weed population are assessed in more general terms than required in most decision models. Weed density assessment might not be debated so intensely if the necessary accuracy for successful model use was understood. Determining the value of assessing weed abundance for making decisions with models would help developers identify the situations for which quantifying weeds is cost-effective. For situations in which it appears likely that a quantitative assessment will never be cost-effective, developers could focus on modifying models to use the type of information about weed populations that users are currently collecting. This will require close collaboration with users. When growers and agricultural consultants in Colorado were interviewed to determine the consistency of density ratings such as low and moderate, it quickly became apparent that the density ratings incorporated more information (such as weed competitive ability) than did weed

density alone (Wiles et al. 1998). Some models would require modification to use these "density ratings" because some of the factors assessed for the density rating are also assessed explicitly as part of the decision model algorithms.

Value of Economic Threshold Models

Scientists developing and implementing bioeconomic models have perhaps hindered wide-scale acceptance of these models by an overemphasis on the ability of the models to determine economic thresholds. For entomologists, the risks inherent in applying broad-spectrum insecticides became clear during the 1970s; the dangers of pest resurgence, secondary pest buildup, insecticide resistance, and getting on the "pesticide treadmill" were demonstrated graphically and documented. In weed science, perceptions of risks have been very different. Weed scientists and producers alike have viewed the risks inherent in leaving weeds uncontrolled in any field as too great to be offset by possible increases in net return from not controlling subthreshold populations, especially when the time and costs involved in scouting are considered. Adoption of an economic threshold approach to weed management has been much slower than that for insect management. O'Donovan (1996) and Swanton et al. (1999) review economic threshold work in weed science and discuss both the difficulties and the possibilities for this approach.

There are certain situations in which a zero threshold makes sense: for example, if a weed is an invading species and there is hope of eliminating it before it takes hold in the field (although if no knowledgeable person is scouting the field, we wonder how the invading species will be discovered before it becomes established); if there are no effective and economical control measures available for use in the following crop; if the crops grown in a field are of high value and the grower is committed to doing whatever it takes to prevent weed escapes; and if even a very low population affects crop quality in unacceptable ways. Certainly, deciding not to control weeds in a field based on a recommendation from an economic threshold model is dangerous if weed densities have not been adequately determined through scouting.

However, we think that in most cases, the use of an economic threshold makes sense. More than 50 yr of applying broad-spectrum herbicides every year to every field does not appear to have reduced weed populations in most fields to zero. National statistics indicate that herbicides are being applied to more than 95% of the acreage of most field crops every year (National Agricultural Statistics Service 2001). Instances of documented herbicide resistance are numerous. Heap (2002) reports that 257 resistant weed biotypes had been found worldwide by March 2002, up from 233 in February 2000 (Heap 2000 as quoted in Hall et al. 2000). O'Donovan (1996) states that there may be more risk associated with prophylactic spraying than that associated with not spraying in terms of lost revenue, environmental damage, and possible development of resistant weed populations. He notes that many of the fears associated with the use of single-season thresholds are probably unfounded. Several factors may lead to an overestimation of potential yield loss by economic threshold models, such as the assumption of uniform weed spatial distribution, the assumption that yield loss for late-emerging weeds is the same as for those that

emerge with the crop, narrower row widths and improved crop stands that reduce weed competitiveness, faster-growing, more competitive crop varieties, and caution on the part of model developers that causes them to increase the CIs for troublesome weed species. All these serve to lower the calculated economic threshold and reduce the risk that growers will mistakenly decide not to spray on the basis of a model recommendation.

We firmly believe that bioeconomic decision models, combined with scouting, can provide valuable assistance even to those who reject the economic threshold approach to weed management. Wiles et al. (1992a) noted that mistakes in herbicide selection at weed densities that are well above the threshold could be costly. Even broad spectrum herbicides are not equally effective against all species, and for many situations there may be no treatment that is 100% effective against all the species that are present. Models that consider the relative densities and competitive abilities of different species and the efficacy of each treatment against each species can assist decision makers in determining which of the available treatments will best help them achieve their goal of minimizing weed problems in current and future crops.

Although the availability of glyphosate-resistant crops has helped growers control many troublesome weed populations, the availability of these crops has not made bioeconomic decision models unnecessary. Large acreages are still planted to crops for which glyphosate-resistant varieties are not now, and may never be, available. Glyphosate does not control all weed species equally well, and mixtures of glyphosate with other herbicides may be necessary for better control of some species. The 2001 North Carolina Agricultural Chemicals Manual (North Carolina State University 2001), for example, notes that several species common to the state are not well controlled by glyphosate and that nine other herbicides can be mixed with at least some brands of glyphosate to provide better control of these weeds in soybean. Glyphosate-resistant weed biotypes have also been documented (e.g., Powles et al. 1998; VanGessel 2001). In addition, volunteer glyphosate-resistant crops may cause problems in a following glyphosate-resistant crop. Decision makers who do not carefully assess weed populations, who follow one glyphosate-resistant crop with another, and who assume glyphosate is the appropriate treatment for every field may suffer unanticipated yield losses and weed population buildups. A decision model can assist users in determining if planting a glyphosate-resistant crop makes sense for a particular field, if another herbicide should be used in addition to, or instead of, glyphosate to maximize weed control or improve economic returns and if so, the appropriate herbicide and rate to use.

How Should Models be Evaluated?

Weed management decision models must be evaluated from three perspectives. Are the predictions biologically reasonable? Do the predictions help users make better decisions than they would otherwise? Is the model convenient and easy to use? How weed management decision models have been evaluated was characterized by reviewing 14 articles describing the evaluation of six different models.

Typical validation of a biological model consists of comparisons of model predictions and observed values. Observed

values may be from the literature or experiments designed specifically to provide validation data. For weed management decision models, predictions such as extent and pattern of emergence, weed control, and crop yield loss can be validated in this way, although validation has been rare. In the 14 studies reviewed, observed and predicted values were compared for crop yield loss in six studies (Berti and Zanin 1997; Coble and Mortensen 1992; Monks et al. 1995; Rankins et al. 1998; Shaw et al. 1998; White and Coble 1997) and efficacy in one study (Shaw et al. 1998). Only one study was designed specifically for validation (White and Coble 1997). Appropriate data for validation are limited in the literature and expensive and time-consuming to obtain. Moreover, any available data are usually needed for model development.

Validating the recommendations of weed management decision models may be more feasible than validating predictions of weed ecology, control, and population dynamics. Validation of recommendations uses expert opinion rather than data, the combinations of weed species and conditions for the evaluations are selected, and specifying the required accuracy for each type of prediction is avoided. In practice, biological predictions of a weed management decision model only have to be accurate enough to generate the right recommendations. To validate the recommendations, model recommendations are compared with the experts' recommendations, and when the recommendations differ significantly, biological predictions are examined to determine the cause. Validation of recommendations has been done informally for many models, but a formal case study could be done with recommendations compared for a selected set of common, problematical, and unusual situations.

In reality, only a small subset of the predictions and recommendations of a weed management decision model can be validated, given the numerous possible situations to test as a result of the large number of weeds and treatments included in most models. For example, a weed management decision model for corn, based on the Colorado Weed Management Guide (Beck et al. 2000), would include 16 weed species, and 15 preemergence, 17 preplant, and 32 post-emergence herbicides. Fortunately, some confidence in the predictions and recommendations of weed management decision models is reasonable with little validation. Current decision models do not incorporate complex biological interactions or environmental influences, biology is modeled using expert opinion or equations developed from replicated field trials, and developers and experts continually evaluate predictions on the basis of their understanding of weed ecology, management, and population dynamics.

A weed management decision model that predicts weed control and ecology well may not necessarily help users make better decisions. Additional evaluation with emphasis on decision makers' current choices for management is needed. The improvement in decision making using a model was evaluated in some sense with several different approaches in the 14 studies. Ideally, results of management recommended by the model and a decision maker (grower) should be compared on paired, large areas within a grower's field, but only two experiments made this comparison (Berti and Zanin 1997; Lybecker et al. 1991b). Many experiments were conducted on research farms and used a locally popular or standard management practice to represent the grower's

selection of management (Buhler et al. 1996, 1997; Forcella et al. 1996; Hoffman et al. 1999a, 1999b; Scott et al. 2001). In experiments that did not include a standard practice, model-recommended management was compared with the management recommended by an expert (Monks et al. 1995; Rankins et al. 1998; Shaw et al. 1998) or another model (Rankins et al. 1998; Renner et al. 1999; Shaw et al. 1998). Management outcomes evaluated in all experiments were crop yield, herbicide use, and an economic measure such as profit minus herbicide cost. Economic criteria were the principal measures of improvement in decision making from using the model. Multiyear evaluations of weed management decision models with assessments of the seed bank or weed population have highlighted potential increases in problem weeds (Hoffman et al. 1999a, 1999b). The environmental effect of recommended herbicide use was assessed in two studies (Berti and Zanin 1997; Forcella et al. 1996).

There is no clear evidence of how well these studies have measured the improvement in decision making with a model. Both on-farm comparison of model- and grower-recommended management and research station comparison of model recommendations to a standard practice have pitfalls. On-farm comparison of grower- and model-recommended management can be confounded by the spatial variability of weed populations so that management of essentially different weed populations is compared. Yet, a standard practice may not be the management a grower would have selected with information about the weed population in the plot. Moreover, a single measure will not likely capture what decision makers will consider to be an improvement in management from using a model. Multicriteria indices may be needed.

Adoption is the ultimate evaluation for a weed management decision model. Decision makers constantly make changes in weed management strategies and tactics and have their own methods for evaluating these changes. A model must not only improve decision making over current practice, but using the model must be easy, convenient, and fast, including assessment of the weed population. Growers, consultants and other decision makers, not scientists, evaluate the ease and convenience of using a model. The most successful models were developed with informal and formal discussions of the model and management practices with growers, consultants, and other decision makers throughout model development.

No systematic procedure for evaluating weed management decision models emerges from the reviewed experiments. However, the evaluations identified model weaknesses and potential solutions, gave some indication of the value of a model to a grower for decision making, and delineated appropriate biological and management conditions for the use of a model. Minor changes could improve the information obtained from the evaluations. For example, adjusting model parameters for regional differences in weed biology before evaluation would ensure that the experiment validates model performance rather than regional differences in weed biology. A grower-recommended treatment could be included along with a standard practice for evaluations not done in growers' fields. However, high quality and efficient evaluation of models require more fundamental changes. Evaluation must be accepted as a necessary component of model development with the three types of eval-

uation planned, with funding identified, early in model development. Evaluation must be recognized as a scientific activity that provides valuable information to others besides the group developing the model. Mechanisms for publishing case studies for validation, work with formal users groups on the design of models, and similar evaluations must be found. Finally, model developers and those evaluating models must cooperate more closely so that performance problems of a model can be identified, the significance determined, and resolutions found long before the article describing the evaluation is published.

Keys to Model Sustainability and Success

Long-term sustainability of modeling efforts is a critical concern for most of those involved in model development, testing, and implementation in the United States. Initial development is very expensive and involves a commitment of resources for programming, data collection, documentation, and field validation. Improving existing models and updating databases as new information becomes available and as new management practices are adopted, reprogramming as computer-operating systems and capabilities change, informing and training potential users, distributing models, and providing technical support are also extremely costly and are not supported so easily through research funding or short-term grants. Salaries have to be competitive with the private sector to attract and retain talented computer programmers. The competitive grant process is primarily designed to foster new ideas rather than to support incremental improvements and maintenance of existing models. Faculty are generally rewarded for innovation, not maintenance activities. Developers and distributors of a number of models have indicated that the lack of stable funding has been a problem (SOYHERB, K. A. Renner, personal communication; Ohio State Herbicide Selector, Mark Loux, personal communication; GWM, L. J. Wiles, personal communication; WeedMAK, J. D. Green, personal communication; AgroManager, Denise Maurice, personal communication).

The success of WeedSOFT[™] (Krishnan et al. 2001b) and the PC-Plant Protection decision support system in Denmark (Murali et al. 1999) indicate the value of stable funding, a plan for distribution, and involvement of the end user in model development, testing, and evaluation. From its beginnings, WeedSOFT[™] development and implementation involved a team of research and extension faculty and a listening group of 20 consultants. WeedSOFT[™] is currently in the hands of 400 users (A. R. Martin, personal communication). The PC-Plant Protection system is distributed by the Danish Agricultural Advisory Centre and was developed in collaboration with the Danish Institute of Agricultural Science. By March 1999, 2,051 farmers had purchased the system, and a survey performed in 1996 showed that the system had been well accepted by farmers who had used the system: 89% of respondents had used the weed control model, and 43% thought that the PC-Plant Protection system had saved them enough money to pay for a single normal dosage requirement of an insecticide or herbicide (Murali et al. 1999).

Given the limited resources available for developing and maintaining decision support systems, there is a need for weed scientists from different locations and agencies to work together, yet weed problems and solutions clearly vary from

place to place. Realizing this, developers of GWM, HADSS[™], and WeedSOFT[™] have developed mechanisms that allow weed scientists in other locations to modify program databases: adding and removing weed species, adjusting weed CIs, changing treatment rates and efficacies, and modifying other information as necessary (Krishnan et al. 2001a; Wiles et al. 1996; Wilkerson et al. 2001). This approach has risks, as well as the obvious advantages: if funding ends at the lead institution, then cooperative efforts at all locations will suffer; each cooperator will have less ability to modify the program to reflect local needs and wishes than would be the case if each researcher had sole responsibility for model development and updating. Nevertheless, recent national and regional projects, funded by the U.S. Department of Agriculture, that involved cooperators from 18 states to customize, validate, and implement HADSS[™] and WeedSOFT[™] give hope that this approach will succeed.

Carefully structured public-private partnerships may be another mechanism for distributing, maintaining, supporting, and updating weed management decision models. A partnership could be structured so that the public agency retains ownership and responsibility for the scientific content of the model. The private partner could be granted an exclusive right to sell the model and have the responsibility for promotion, distribution, user support (except for scientific issues), maintenance of the interface (updating it for advancements in computer software and hardware), and updating some databases in cooperation with the public partner (M. Weltz, personal communication). This approach will require developers to demonstrate commercial value for a decision model and to structure agreements so that the sharing of the model for research use is not hindered and the appearance of endorsement of commercial software by a public agency is avoided.

In addition to long-term funding (whether this proves to be through state, federal, private, or some combination of these funding sources), there must also be stability in institutional commitment to the development effort: can the modeling effort survive the retirement or relocation of any one individual? To have any hope of achieving this level of stability, model development must involve a team that includes weed science experts, professional programmers, and end users. Ultimately, success will depend on the ability of model supporters to demonstrate not only to clientele but equally importantly to the weed science community that these models can truly assist in making decisions that increase profitability for users, reduce the application of unnecessary or inappropriate herbicides, and promote weed management based on sound biological and ecological principles.

Possibilities and Predictions

The first all-purpose computer, the ENIAC, was unveiled in 1946, only 5 yr before the first issue of *Weeds*, the predecessor to *Weed Science*. In the intervening years, computer capabilities for storing, organizing, analyzing, displaying, and transmitting information have increased to the point that computers have become essential tools for virtually all weed scientists and have become an integral part of our society. Only in the past 5 yr, with the development of palmtop computers and widely available Internet access, has

this technology become good enough that utilizing decision models in weed management has become truly practical. Use of computers in the United States increased from 38% of all farms in 1997 to 55% in 2001, whereas Internet use grew from 13% of all farms to 43% (Economic Research Service 2001). Several weed management models are available over the World Wide Web: they can be downloaded from the website for installation on a personal computer (e.g., DesHerb, Claude J. Bouchard, personal communication; WeedMAK, J. D. Green, personal communication). There are several advantages to distributing models in this way rather than by diskette or CD, including cost, time, and the ability to update the program or databases on the server and make this updated version instantly available to all users. One drawback is that it is still necessary to inform users of the updates. Developers can address this issue by having a downloaded program expire after a period of time so that a user is forced to download an updated version or by sending e-mail update notices to registered users.

In the future, Web-based applications, programs that run on a server and can be accessed by anyone with an Internet connection and a Web browser, will become more common. Pl@ntInfo, a Web-based decision support system developed by collaboration between the Danish Institute of Agricultural Sciences and the Danish Agricultural Advisory Centre and launched in 1996, is an early indicator of just how powerful the World Wide Web may be as a method for providing decision support to farmers and their advisors (Jensen et al. 2000). This system contains several decision support models (apparently none dealing with weed control), as well as news of crop production and weather information. During the 3-mo period May 6 to August 5, 1998, the system had 617,340 external hits ($6,710\text{ d}^{-1}$) and 23,029 visits by subscribers (250 d^{-1}). Both farmer and advisor subscribers to the system were judged to be quite dedicated in using the system, with the most complex decision model (irrigation) being the most popular with farmers and the record-keeping function being the most popular with advisors.

At least one Web-based weed management decision aid is now available. Web HADSS[®], a Web-based version of HADSS[®], was launched in the spring of 2001 and made more than 700 recommendations in its first season despite limited publicity (Sturgill et al. 2001a). Creation of Web-based applications presents some new challenges to program developers. Two primary ones are the difficulty of checking user input information for validity and programming for a multiuser environment. Web-based applications are still somewhat limited in functionality compared with desktop programs. Maintenance of a Web-accessible server capable of providing recommendations rapidly to a large number of users is an additional expense, but Web-based applications have several advantages. For example, they do not require a user to load any software on a personal machine, which greatly reduces technical support needs and avoids taking up space on the user's computer with a program that may be needed only a few times during the growing season. Also, user inputs can be stored in a database on the server. It is then possible for program developers to duplicate runs that have been made. Results of these runs can be analyzed to determine if the recommendations appear reasonable and whether sufficient information was provided to the user to

make an informed decision. This ability can spotlight user misunderstandings about how the model functions.

The use of the Internet to provide agricultural information to producers, extension agents, and other advisors will continue to expand. The way this information is provided to clientele will continue to grow in sophistication, taking advantage of the unique and rapidly improving capabilities of this medium. As the format for information delivery shifts from on-line delivery of text documents (similar to print bulletins) to delivery in searchable databases, the dividing lines between information delivery and models will blur. Web-based decision support systems will provide easy access to case-specific information related to all aspects of weed management: weed identification, suitable weed control options, optimal timing of control measures, potential for herbicide injury, crop rotation and other label restrictions, chemical modes of action, possibility for herbicide resistance, and potential for environmental damage, among others. Consideration of biological and economic aspects of weed control will form just one part of these systems.

The availability of powerful palmtop computers is already allowing decision makers to enter data while in the field and rapidly obtain a recommendation (Sturgill et al. 1999). In the future, assistance with weed identification can be provided as well, either directly with pictures and text stored on the palmtop or through wireless access to a network. Small, lightweight digital cameras, connected to the palmtop computers, eventually will allow rapid identification of weeds discovered in a particular field, either through viewing over a wireless connection by a human expert or through customized weed recognition software. The necessity for counting weeds at multiple locations within a field also may be obviated by the availability of sophisticated but inexpensive sensors and the development of software to analyze digital images. Progress is being made in distinguishing weeds from crop and soil and in weed identification based on spectral or shape characteristics (e.g., Andreasen et al. 1997; El-Faki et al. 2000; Wang et al. 2001; Woebbecke et al. 1995a, 1995b). Through the voice-recording capabilities of palmtop computers and voice-recognition software residing either on these machines on desktop or Web-based systems, scouts will be able to enter relevant field information much more easily than at present.

Technology that automates the assessment of weed populations will reduce the cost, labor, and time requirements for scouting and data entry that currently constrain the use of models in some situations. Automation may also increase the accuracy of weed population assessment. Decision models modified to use weed population information generated by this technology will be critical for the practical implementation of site-specific weed management. Eventually, economically feasible and time-efficient methods for determining the identity and spatial distribution of weeds within a field will be perfected, whether they be ground, airplane, or satellite based. Whatever technology is used to assess a weed population and whatever site-specific application technology is used (variable rate or sensor based), decision aids can play an important role in determining the appropriate herbicide(s) to apply.

Will the availability of new weed control technologies obviate the need for comprehensive decision support systems? Probably not, given the dynamic and diverse nature

of the agroecosystem. Although producers hope for the "magic bullet" that will solve all weed management problems, we doubt that any magic bullet will be effective for very long. Overuse and misuse of any technology or weed management technique will have unforeseen and unintended consequences, will promote nonpests to pest status, and will lead to shifts in pest species dynamics (time of emergence, growth habit, etc.). This will require the new technology to be supplemented with other control measures and may eventually lead to its abandonment in some situations. David P. Davis (personal communication) is involved in a modeling project to help answer questions about how long a grower can remain in the CLEARFIELD rice (*Oryza sativa* L.) system because of fear that growers may abuse it, potentially limiting its usefulness. Comprehensive decision support systems, based on as much expert knowledge and research information as possible, can help ensure that new and powerful weed control technologies are not rapidly lost through overuse and misuse.

There are those who think that our efforts in developing weed management decision tools are doomed because we may be addressing a "problem" that the grower does not perceive (Kamp 1999). The perception is that weed management decision models are not being adopted. Closer to reality is that many models have not been made available to growers because of lack of infrastructure for maintenance, distribution, marketing, and support, but a few models are being adopted, albeit slowly. We have been encouraged greatly during the past 3 yr by the willingness of weed scientists from 18 states to develop customized versions of either HADSS[™] or WeedSOFT[™], to evaluate these in field experiments, to work with growers and extension agents to evaluate these programs further, and to work with model developers to improve the programs. However, whether weed management decision models will be adopted widely is still far from certain. Perhaps modelers are similar to farmers in that they must be optimists in order to survive. At any rate, we remain convinced that weed management decision models have a valuable role to play in classroom and extension education and in promoting sound weed management decisions. We also recognize the tremendous challenges, but our optimism is not unfounded. Technological improvements will make obtaining field-specific information and delivering recommendations easier. Knowledge of weed ecology and population dynamics will continue to expand, and decision models will be needed to incorporate this knowledge into integrated management systems. The next generation of decision makers will be more technically savvy, and using a model will be accepted more readily as part of the decision-making process. As models are used more extensively, funding for maintenance and support should be easier to obtain.

The greatest challenge, however, is neither technological nor scientific. Rather, by far the greatest challenge remains in convincing growers and those that advise them that the benefits of using a weed management decision aid justify the effort. We also need to demonstrate this to ourselves to justify our continuing efforts. We must begin to emphasize the overall capabilities of decision models, not just their ability to calculate an economic threshold. We must do a better job of explaining the tasks for which they are and are not well suited. Weed management decision models were over-

sold initially, but now expectations of what models will do for decision makers are becoming more realistic. Decision models can never replace the decision maker nor can they incorporate all the factors that should be considered. Model developers can only hope to provide information that is relevant to the decision and to organize and present that information in a way that is most useful and reflects, as much as possible, the knowledge and experience of weed science experts.

Acknowledgments

We thank Dr. Robert Zimdahl for giving us the opportunity to pause and reflect on the current and future status of weed management decision models. We also thank reviewers of earlier drafts whose thoughtful comments helped improve this manuscript. Finally, we thank all the weed scientists who took the time to respond to our Web survey.

Literature Cited

- Aarts, H.F.M. and C.L.M. de Visser. 1985. A management information system for weed control in winter wheat. Proc. 1985 Br. Crop Prot. Conf. Weeds 2:679–686.
- Allen, W. A. and E. G. Rajotte. 1990. The changing role of extension entomology in the IPM era. Annu. Rev. Entomol. 35:379–397.
- Ambrosia, L., J. Dorado, and J. P. Del Monte. 1997. Assessment of the sample size to estimate the weed seedbank in soil. Weed Res. 37:129–137.
- Anderson, J. M. and C. G. McWhorter. 1976. The economics of common cocklebur control in soybean production. Weed Sci. 24:397–400.
- Andreasen, C., M. Rudemo, and S. Sevestre. 1997. Assessment of weed density at an early stage by use of image processing. Weed Res. 37:5–18.
- Auld, B. A. and C. A. Tisdell. 1987. Economic thresholds and response to uncertainty in weed control. Agric. Syst. 25:219–227.
- Barrentine, W. L. 1974. Common cocklebur competition in soybeans. Weed Sci. 22:600–603.
- Beck, K. G., S. K. MacDonald, S. J. Nissen, and P. Westra. 2000. 2000 Colorado Weed Management Guide: Field and Vegetable Crops. Fort Collins, CO: Colorado State University Cooperative Extension Service.
- Bennett, A. C., G. G. Wilkerson, and M. C. Sturgill. 2000. Implementation of a decision support system for the southern US. Weed Sci. Soc. Am. Abstr. 40:37.
- Berti, A. and G. Zanin. 1994. Density equivalent: a method for forecasting yield loss caused by mixed weed populations. Weed Res. 34:327–332.
- Berti, A. and G. Zanin. 1997. GESTINF: a decision model for post-emergence weed management in soybean (*Glycine max* (L.) Merr.). Crop Prot. 16:109–116.
- Black, I. D. and C. B. Dyson. 1993. An economic threshold model for spraying herbicides in cereals. Weed Res. 33:279–290.
- Blouch, R. and J. Fuhs. 1953. The influence of soil type on the selective action of chloro-IPC and sodium TCA. Weeds 2:119–124.
- Buhler, D. D., R. P. King, S. M. Swinton, J. L. Gunsolus, and F. Forcella. 1996. Field evaluation of a bioeconomic model for weed management in corn (*Zea mays*). Weed Sci. 44:915–923.
- Buhler, D. D., R. P. King, S. M. Swinton, J. L. Gunsolus, and F. Forcella. 1997. Field evaluation of a bioeconomic model for weed management in soybean (*Glycine max*). Weed Sci. 45:158–165.
- Burrough, P. A. 1991. Sampling designs for quantifying map unit composition. Pages 89–125 in M. J. Mausbach and L. P. Wilding, eds. Spatial Variabilities of Soils and Landforms. SSSA Special Publication no. 28. Madison, WI: Soil Science Society of America.
- Coble, H. D. 1986. Development and implementation of economic thresholds for soybean. Pages 295–307 in R. E. Frisbie and P. L. Adkisson, eds. CIPM: Integrated Pest Management on Major Agricultural Systems. College Station, TX: Texas A&M University.
- Coble, H. D. and D. A. Mortensen. 1992. The threshold concept and its application to weed science. Weed Technol. 6:191–195.
- Coble, H. D. and R. L. Ritter. 1978. Pennsylvania smartweed (*Polygonum pennsylvanicum*) interference in soybeans (*Glycine max*). Weed Sci. 26:556–559.

- Cousens, R. 1985. A simple model relating yield loss to weed density. *Ann. Appl. Biol.* 107:239–252.
- Cousens, R., P. Brain, J. T. O'Donovan, and P. A. O'Sullivan. 1987a. The use of biologically realistic equations to describe the effects of weed density and relative time of emergence on crop yield. *Weed Sci.* 35: 720–725.
- Cousens, R., S. R. Moss, G. W. Cussans, and B. J. Wilson. 1987b. Modeling weed populations in cereals. *Rev. Weed Sci.* 3:93–112.
- Doyle, C. J. 1991. Mathematical models in weed management. *Crop Prot.* 10:432–444.
- Doyle, C. J. 1997. A review of the use of models of weed control in integrated crop protection. *Agric. Ecosyst. Environ.* 64:165–172.
- Economic Research Service. 2001. *Agricultural Outlook*. Washington, DC: AGO 286, USDA, ERS.
- El-Faki, M. S., N. Zhang, and D. E. Peterson. 2000. Weed detection using color machine vision. *Trans. Am. Soc. Agric. Eng.* 43:1969–1978.
- Ennis, W. B., Jr. 1958. The challenges of modern weed control. *Weeds* 6: 363–369.
- Ennis, W. B., Jr. 1960. Use of herbicides, growth regulators, nematocides and fungicides. Pages 17–27 in *The Nature and Fate of Chemicals Applied to Soils, Plants and Animals*. Washington, DC: USDA-ARS.
- Forcella, F., R. P. King, S. M. Swinton, D. D. Buhler, and J. L. Gunsolus. 1996. Multi-year validation of a decision aid for integrated weed management in row crops. *Weed Sci.* 44:650–661.
- Foy, C. L. 1954. Effectiveness of isopropyl *N*-(3-chlorophenyl) carbamate as a selective preemergence herbicide in cotton. *Weeds* 3:282–291.
- Freed, V. H. 1951. Some factors influencing the herbicidal efficacy of isopropyl *N* phenyl carbamate. *Weeds* 1:48–60.
- Gerowitt, B. and R. Heitefuss. 1990. Weed economic thresholds in cereals in the Federal Republic of Germany. *Crop Prot.* 9:323–331.
- Gold, H. J., J. Bay, and G. G. Wilkerson. 1996. Scouting for weeds, based on the negative binomial distribution. *Weed Sci.* 44:504–510.
- Gotway, C. A., R. B. Ferguson, and G. W. Hergert. 1996. The effects of mapping and scale on variable-rate fertilizer recommendations for corn. Pages 321–330 in P. C. Robert, R. H. Rust, and W. E. Larson, eds. *Precision Agriculture*. Minneapolis, MN: American Society of Agronomy.
- Hall, J. C., L. L. Van Eerd, S. D. Miller, M.D.K. Owen, T. S. Prather, D. L. Shaner, M. Singh, K. C. Vaughn, and S. C. Weller. 2000. Future research directions for weed science. *Weed Technol.* 14:647–658.
- Harsh, S. B., J. W. Lloyd, and L. R. Borton. 1989. Models as an aid to decision making. *Acta Hort.* 248:27–48.
- Heap, I. 2000. The International Survey of Herbicide Resistant Weeds. Available at www.weedscience.com. Accessed: February 15, 2000.
- Heap, I. 2002. The International Survey of Herbicide Resistant Weeds. Available at www.weedscience.com. Accessed: March 01, 2002.
- Hoffman, M. L., D. D. Buhler, and M.D.K. Owen. 1999a. Weed populations and crop yield response to recommendations from a weed control decision aid. *Agron. J.* 91:386–392.
- Hoffman, M. L., D. D. Buhler, and M.D.K. Owen. 1999b. Multi-year evaluations of model based weed control under variable crop and tillage conditions. *J. Crop Prod.* 2:207–224.
- Holstun, J. T., Jr., O. B. Wooten, Jr., C. G. McWhorter, and G. B. Crowe. 1960. Weed control practices, labor requirements and costs in cotton production. *Weeds* 8:232–243.
- Indyk, H. W. 1957. Pre-emergence weed control in soybeans. *Weeds* 5: 362–370.
- Jensen, A. L., P. S. Boll, I. Thysen, and B. K. Pathak. 2000. Pl@ntInfo—a web-based system for personalised decision support in crop management. *Comput. Electron. Agric.* 25:271–293.
- Kamp, J.A.L.M. 1999. Knowledge based systems: from research to practical application: pitfalls and critical success factors. *Comput. Electron. Agric.* 22:243–250.
- Keisling, T. C., L. R. Oliver, R. H. Crowley, and F. L. Baldwin. 1984. Potential use of response surface analyses for weed management in soybeans (*Glycine max*). *Weed Sci.* 32:552–557.
- King, R. P., D. W. Lybecker, E. E. Schweizer, and R. L. Zimdahl. 1986. Bioeconomic modeling to simulate weed control strategies for continuous corn (*Zea mays*). *Weed Sci.* 34:972–979.
- King, R. P., S. M. Swinton, D. W. Lybecker, and C. A. Oriade. 1998. The economics of weed control and the value of weed management information. Pages 25–41 in J. L. Hatfield, D. D. Buhler, and B. A. Stewart, eds. *Integrated Weed and Soil Management*. Chelsea, MI: Ann Arbor Press.
- Krishnan, G., D. A. Mortensen, A. R. Martin, and L. B. Bills. 2001a. Regionalizing a locally adapted weed management decision support system. *Weed Sci. Soc. Am. Abstr.* 41:41.
- Krishnan, G., D. A. Mortensen, A. R. Martin, L. B. Bills, A. Dieleman, and C. Neeser. 2001b. WeedSOFT: a state of the art weed management decision support system. *Weed Sci. Soc. Am. Abstr.* 41:41.
- Kropff, M. J. and C.J.T. Spitters. 1991. A simple model of crop loss by weed competition from early observations on relative leaf area of the weeds. *Weed Res.* 31:97–106.
- Krueger, D. W., G. G. Wilkerson, H. D. Coble, and H. J. Gold. 2000. An economic analysis of binomial sampling for weed scouting. *Weed Sci.* 48:53–60.
- Kwon, T. J., D. L. Young, F. L. Young, and C. M. Boerboom. 1995. PALWEED:WHEAT: a bioeconomic decision model for postemergence weed management in winter wheat (*Triticum aestivum*). *Weed Sci.* 43:595–603.
- Kwon, T. J., D. L. Young, F. L. Young, and C. M. Boerboom. 1998. PALWEED:WHEAT II: revision of a weed management decision model in response to field testing. *Weed Sci.* 46:205–213.
- Lotz, L.A.P., S. Christensen, D. Cloutier, et al. 1996. Prediction of the competitive effects of weeds on crop yields based on the relative leaf area of weeds. *Weed Res.* 36:93–101.
- Lundkvist, A. 1997. Weed management models: a literature review. *Swed. J. Agric. Res.* 27:155–166.
- Lybecker, D. W., E. E. Schweizer, and R. P. King. 1991a. Weed management decisions based on bioeconomic modeling. *Weed Sci.* 39:124–129.
- Lybecker, D. W., E. E. Schweizer, and P. Westra. 1991b. Computer aided decisions for weed management in corn. Pages 234–239 in *Proceedings of the Western Agricultural Economics Association*. Portland, OR: Western Agricultural Economics Association.
- Lybecker, D. W., E. E. Schweizer, and P. Westra. 1993. Computer aid for managing weeds in corn. *Proc. Conf. Agric. Res. Prot. Water Qual.* 2:295–297.
- Marra, M. C. and G. A. Carlson. 1983. An economic model for weeds in soybeans (*Glycine max*). *Weed Sci.* 31:604–639.
- Martin, A. R., D. A. Mortensen, and L. Bills. 2001. Computerized weed management decision aids. *Weed Sci. Soc. Am. Abstr.* 41:114–115.
- Metcalf, R. L. 1980. Changing role of insecticides in crop protection. *Annu. Rev. Entomol.* 25:219–256.
- Monks, C. D., D. C. Bridges, J. W. Woodruff, T. R. Murphy, and D. J. Berry. 1995. Expert system evaluation and implementation for soybean (*Glycine max*) weed management. *Weed Technol.* 5:535–540.
- Mortensen, D. A. and H. D. Coble. 1991. Two approaches to weed control decision-aid software. *Weed Technol.* 5:445–452.
- Mortensen, D. A., A. R. Martin, F. W. Roeth, T. E. Harvill, R. W. Klein, G. A. Wicks, R. G. Wilson, D. L. Holshouser, and J. W. McNamara. 1993. *NebraskaHERB Version 3.0 User's Manual*. Lincoln, NE: Department of Agronomy, University of Nebraska.
- Mortensen, D. A., A. R. Martin, F. W. Roeth, et al. 1999. *WeedSOFT Version 4.0 User's Manual*. Lincoln, NE: Department of Agronomy, University of Nebraska.
- Murali, N. S., B.J.M. Secher, P. Rydahl, and F. M. Andreasen. 1999. Application of information technology in plant protection in Denmark: from vision to reality. *Comput. Electron. Agric.* 22:109–115.
- National Agricultural Statistics Service. 2001. *Agricultural Chemical Usage: 2000 Field Crops Summary*. Washington, DC: Agricultural Statistics Board, USDA, NASS.
- Norris, R. F. 1999. Ecological implications of using thresholds for weed management. *J. Crop Prod.* 2:31–58.
- North Carolina State University. 2001. *The 2001 North Carolina Agricultural Chemicals Manual*. Raleigh, NC: College of Agriculture and Life Sciences, NCSU. 500 p.
- Nyland, R. E., D. C. Nelson, and D. H. Dinkel. 1958. Comparative costs of weeding onions by hand or with monuron, CIPC, and CDAA. *Weeds* 6:304–309.
- O'Donovan, J. T. 1996. Weed economic thresholds: useful agronomic tool or pipe dream? *Phytoprotection* 77:13–28.
- O'Donovan, J. T., J. C. Newman, K. N. Harker, R. E. Blackshaw, and D. W. McAndrew. 1999. Effect of barley plant density on wild oat interference, shoot biomass and seed yield under zero tillage. *Can. J. Plant Sci.* 79:655–662.
- Pannell, D. J. 1990. An economic response model of herbicide application for weed control. *Aust. J. Agric. Econ.* 34:223–241.
- Pannell, D. J., V. Stewart, A. Bennett, M. Monjardino, C. Schmidt, and S. Powles. 2000. RIM: A bioeconomic Model for Integrated Weed Management. SEA Working Paper 00/10: Web page: <http://>

- www.general.uwa.edu.au/u/dpannell/dpap0010.htm. Nedlands, Australia: Agricultural and Resource Economics, University of Western Australia.
- Powles, S. B., D. F. Lorraine-Colwill, J. J. Dellow, and C. Preston. 1998. Evolved resistance to glyphosate in rigid ryegrass (*Lolium rigidum*) in Australia. *Weed Sci.* 46:604–607.
- Rankins, A., D. R. Shaw, and J. D. Byrd. 1998. HERB and MSU-HERB field validation for soybean (*Glycine max*) weed control in Mississippi. *Weed Technol.* 12:88–96.
- Renner, K. A., S. M. Swinton, and J. J. Kells. 1999. Adaptation and evaluation of the WEEDSIM weed management model for Michigan. *Weed Sci.* 47:338–348.
- Rydahl, P. 1999. Optimising mixtures of herbicides within a decision support system. *Proc. 1999 Brighton Conf. Weeds* 3:761–766.
- Schribbs, J. M., D. W. Lybecker, and E. E. Schweizer. 1990. Bioeconomic weed management models for sugarbeet (*Beta vulgaris*) production. *Weed Sci.* 38:436–444.
- Scott, G. H., S. D. Askew, A. C. Bennett, and J. W. Wilcut. 2001. Economic evaluation of HADDS[®] computer program for weed management in nontransgenic and transgenic cotton. *Weed Sci.* 49:549–557.
- Scott, D. H., W. C. Shaw, and R. U. Ruppenthal. 1954. Evaluation of several chemicals for weed control in strawberry fields. *Weeds* 3:192–207.
- Shadbolt, C. A. and L. G. Holm. 1956. Some quantitative aspects of weed competition in vegetable crops. *Weeds* 4:111–123.
- Shaw, D. R., A. Rankins, J. T. Ruscoe, and J. D. Byrd. 1998. Field validation of weed control recommendations from HERB and SWC herbicide recommendation models. *Weed Technol.* 12:78–87.
- Slife, F. W. 1956. The effect of 2,4-D and several other herbicides on weeds and soybeans when applied as postemergence sprays. *Weeds* 4:61–68.
- Stern, V. M. 1973. Economic thresholds. *Annu. Rev. Entomol.* 18:259–280.
- Stern, V. M., R. F. Smith, R. van den Bosch, and K. S. Hagen. 1959. The integrated control concept. *Hilgardia* 29:81–99.
- Stigliana, L. and C. Resina. 1993. SELOMA: expert system for weed management in herbicide-intensive crops. *Weed Technol.* 7:550–559.
- Streibig, J. C. 1989. The herbicide dose-response curve and the economics of weed control. *Proc. 1989 Br. Crop Prot. Conf. Weeds* 3:927–935.
- Sturgill, M. C., G. S. Buol, G. G. Wilkerson, A. C. Bennett, and W. D'mello. 2001a. HADSS: a family of herbicide decision support aids. C00-sturgill134016-D in ASA-CSSA-SSSA Abstracts CD-ROM. Madison, WI: American Society of Agronomy.
- Sturgill, M. C., G. G. Wilkerson, and G. S. Buol. 1999. Pocket HERB: an in-the-field post emergence weed control decision aid. Page 35 in 1999 Abstracts. 91st Annual Meeting. Madison, WI: American Society of Agronomy.
- Sturgill, M. C., G. G. Wilkerson, J. Wilcut, A. C. Bennett, and G. S. Buol. 2001b. HADSS 2001 User's Manual. Research Bulletin 192. Raleigh, NC: Crop Science Department, North Carolina State University.
- Swanton, C. J., S. Weaver, P. Cowan, R. Van Acker, W. Deen, and A. Shreshta. 1999. Weed thresholds: theory and applicability. *J. Crop Prod.* 2:9–29.
- Swinton, S. M., D. D. Buhler, F. Forcella, J. L. Gunsolus, and R. P. King. 1994. Estimation of crop yield loss due to interference by multiple weed species. *Weed Sci.* 42:103–109.
- Swinton, S. M. and R. P. King. 1994. A bioeconomic model for weed management in corn and soybean. *Agric. Syst.* 44:313–335.
- Swinton, S. M. and C. P. Lyford. 1996. A test for choice between hyperbolic and sigmoidal models of crop yield response to weed density. *J. Agric. Biol. Environ. Statist.* 1:97–106.
- VanGessel, M. J. 2001. Glyphosate-resistant horseweed from Delaware. *Weed Sci.* 49:703–705.
- Wang, N., N. Zhang, F. E. Dowell, Y. Sun, and D. E. Peterson. 2001. Design of an optical weed sensor using plant spectral characteristics. *Trans. Am. Soc. Agric. Eng.* 44:409–419.
- White, A. D. and H. D. Coble. 1997. Validation of HERB for use in peanut (*Arachis hypogaea*). *Weed Technol.* 11:573–579.
- Wiles, L. J., S. R. Canner, and Bosley, D. B. 1998. Talking about weed pressure: an interview survey of farmer and crop consultant descriptions of weed density level. *Proc. West. Weed Sci. Soc.* 51:117.
- Wiles, L. J., R. P. King, E. E. Schweizer, D. W. Lybecker, and S. M. Swinton. 1996. GWM: general weed management model. *Agric. Syst.* 50:355–376.
- Wiles, L. J., G. G. Wilkerson, and H. J. Gold. 1992a. Value of information about weed distribution for improving postemergence control decisions. *Crop Prot.* 11:547–554.
- Wiles, L. J., G. G. Wilkerson, H. J. Gold, and H. D. Coble. 1992b. Modeling weed distribution for improved postemergence control decisions. *Weed Sci.* 40:546–553.
- Wilkerson, G. G., G. S. Buol, M. C. Sturgill, and A. C. Bennett. 2001. WeedED Version 4 User's Guide. Research Rep. 191. Raleigh, NC: Crop Science Department, North Carolina State University.
- Wilkerson, G. G., S. A. Modena, and H. D. Coble. 1991. HERB: decision model for postemergence weed control in soybeans. *Agron. J.* 83:413–417.
- Wilkerson, G. G., J. W. Wilcut, A. C. Bennett, M. C. Sturgill, and G. S. Buol. 1999. Herb Version 9.0 User's Manual. Research Bulletin 178. Raleigh, NC: Crop Science Department, North Carolina State University.
- Woebbecke, D. M., G. E. Meyer, K. Von Bargen, and D. A. Mortensen. 1995a. Color indices for weed identification under various soil, residue, and lighting conditions. *Trans. Am. Soc. Agric. Eng.* 38:259–269.
- Woebbecke, D. M., G. E. Meyer, K. Von Bargen, and D. A. Mortensen. 1995b. Shape features for identifying young weeds using image analysis. *Trans. Am. Soc. Agric. Eng.* 38:271–281.

Received November 20, 2001, and approved April 5, 2002.